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Different strokes for different folks? Revealing the physical characteristics of smartphone users from their swipe gestures ☆

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ABSTRACT

Anthropometrics show that the lengths of many human body segments follow a common proportional relationship. To know the length of one body segment – such as a thumb – potentially provides a predictive route to other physical characteristics, such as overall standing height. In this study, we examined whether it is feasible that the length of a person's thumb could be revealed from the way in which they complete swipe gestures on a touchscreen-based smartphone.

From a corpus of approx. 19,000 swipe gestures captured from 178 volunteers, we found that people with longer thumbs complete swipe gestures with shorter completion times, higher speeds and with higher accelerations than people with shorter thumbs. These differences were also observed to exist between our male and female volunteers, along with additional differences in the amount of touch pressure applied to the screen.

Results are discussed in terms of linking behavioural and physical biometrics.

1. Introduction

The ability to accurately link a physical person to their activities conducted in the digital realm is an increasing challenge for our intelligence and law enforcement agencies. The present work was inspired through collaboration with the large multidisciplinary project Super Identity[1] whose overarching aim is to model links between a wide range of physical/digital identity measures in order to build new identity attribution techniques.

The theme of this paper was inspired by a need to address a specific real-world problem: how to identify criminals who conduct their activities using temporary burner mobile phones that are unregistered to them by name. Our main objective is to establish whether touch interaction dynamics can be leveraged to provide usable evidence as to the physical characteristics of their creator.

In this paper, we present initial findings from an exploration into whether it is feasible to infer a single specific physical characteristic of a person – specifically the length of their thumb – from the way in which they perform a common smartphone interaction gesture, the 'swipe'. If such a link could be made, we suggest that by following a route through known proportional relationships between that digit length and other human measurements, we would conceivably be able to infer various other physical characteristics of the person who created the gestures. To provide an example, to possess a long thumb suggests a longer hand length, a longer hand length suggests a longer forearm length and a longer forearm length suggests a taller standing height.

1.1. The use of anthropometrics as a predictive route between segment lengths in the human body

As classically illustrated by Da Vinci in 'Vitruvian Man' (Fig. 1), studies of anthropometrics (e.g. Drillis et al., 1964; Doczi, 1981; Gordon et al., 1989; Fromuth and Parkinson, 2008) have shown that numerous segment lengths of the human body follow a common proportionality, approximating the 'golden ratio' of 1:1.618. This ability to predict the length of one body segment length (e.g. a persons height) from another (e.g. the length of their forearm) has found utility in multiple domains, most notably forensic science and ergonomics.

Such is the importance of access to accurate anthropometrics data for the purposes of human tool and clothing design, large corpura of detailed body measurement data have been collected over the last century. Larger datasets include works conducted by the U.S. Military (e.g. Gordon, 1989; White, 1980; Garrett, 1971) and NASA (e.g. Webb Associates, 1978). The anthropometric data provided by 'Kodak's Ergonomic Design for People at Work' (E.K. Company, 2004) is a frequently cited classic resource within the field of ergonomics and product design.

Analysis of the proportional relationships between various body segment lengths continues to produce the support to forensic and medical science, often to assess their suitability as a usable predictive tool. The ability to predict the length of a missing body segment (e.g. a femur bone) is for example useful in forensic anthropology, where

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[1] SID: an exploration of super-identity, EPSRC. 2011–2015. http://www.southampton.ac.uk/superidentity.

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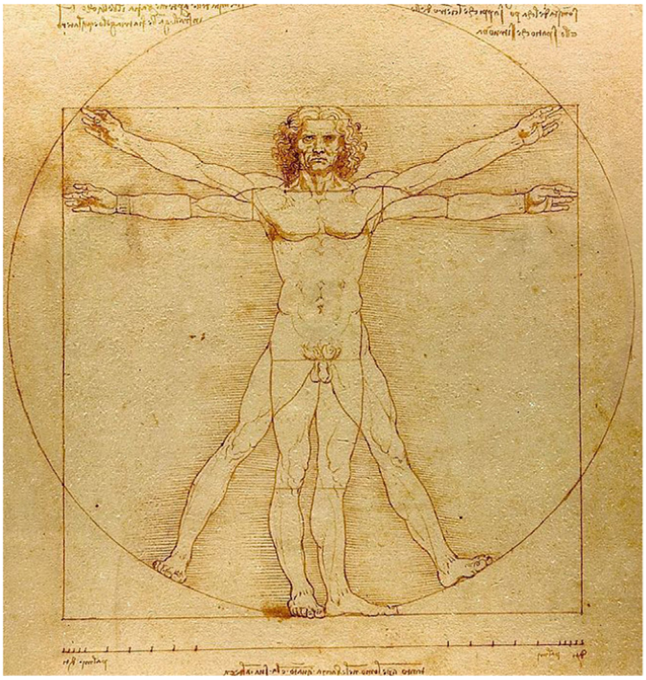

Fig. 1. *The Vitruvian Man*. Leonardo da Vinci, c1490.

the need to perform reconstructions of bodies from incomplete skeletal remains is a frequently encountered task. Results of a number of studies that have specifically considered the hand offer promising evidence that a predictive route from thumb length to larger body segment lengths is available. The close relationship between hand length measurements and standing height has been reported by Ilayperuma et al. (2009), Abdel-Malek et al. (1990), Meadows and Jantz (1992) among others, while similar analyses examining the relationship among hand length, foot length and standing height can be found in Sanli et al. (2005).

1.2. Capturing thumb length to serve as a route to hand length and beyond

When held one-handed, interacting with the touchscreen of a smartphone is naturally restricted to the use of the thumb only. In this paper, we hypothesise that when a smartphone is used in this way, evidence as to the likely length of its user's thumb is revealed by dynamics of their gestural touch interactions (such as their length and drawing speed). If this were indeed the case, it would provide a useful link between what would be considered a behavioural biometric, to a soft physical biometric for that individual.

In the present study, we obtained an accurate measure of the length of each of our participants' thumb, before then capturing a number of their touchscreen *swipe* gestures using an instrumented smartphone. Swipe gestures were drawn and captured in multiple directions. To maximise any potential correspondence between thumb length and the resultant characteristics of swipes created using that thumb, we restricting our participants' interaction with the device to one-handed use only, with the device held in portrait orientation.

The swipe gesture (sometimes referred to as *flick* or *fling*) involves placing a finger or thumb on the screen and – while maintaining contact with the screen – quickly swiping it in the desired direction. Akin to flicking through the pages of a book, the swipe gesture is frequently used to support content navigation, such as navigating a photo album or paging through a list. The swipe gesture was selected for this investigation over other touch gestures (e.g. *drag*, or multitouch gestures such as *pinch-to-zoom*) primarily because of its high frequency of use, but also for its high range of extractable features across a number of dimensions, including length, drawing speed and touch pressure.

1.3. Related work

Biometrics are measures of human characteristics and traits. Biometrics can be physical or behavioural based. Physical biometrics relate to *something a person is*, and can be subclassed into either *soft* or *hard* depending on the degree to which they are unique to a particular group of individuals or a specific individual respectively. An example of a hard physical biometric would be the unique pattern associated with a person's fingerprint or their DNA profile. An example of a soft biometric would be the colour of a person's hair or iris.

A behavioural biometric relates to *something a person does*; the identification of an individual through some unique aspect of their behaviour. Like physical biometrics, behavioural biometrics can also take hard and soft forms. Human–computer interaction research has explored potential sources of behavioural biometric material from a variety of angles, including the way in which individuals type on a keyboard (*keystroke dynamics* e.g. Maxion et al., 2010; Killourhy et al., 2009; Banerjee and Woodard, 2012; Monrose and Rubin, 2000; Zahid et al., 2009), how they use their mouse (Zheng et al., 2011; Shen et al., 2013) and even the way that they walk (Derawi et al., 2010; Ho et al., 2012).

In recent years, the interactive touchscreen has become the dominant input mechanism for a range of mobile computing devices, most notably smartphones and tablets. The ubiquity of these devices, along with rapid advances in the sensitivity and accuracy of touchscreen technology has attracted renewed interest from researchers for their potential as a source of new behavioural biometrics. Of particular interest is whether the dynamics of a given person's touch interaction style are unique enough to provide new user authentication mechanism that are both secure and usable (Kolly et al., 2012). This effort is a response to the increasing concerns of both security researchers including Azenkot et al. (2012) and Ben-Asher et al. (2011) and end-users (Chin et al., 2012) that the security/usability tradeoff of existing user authentication schemes for these new mobile devices is not optimal, particularly when taking into account the broad ways in which these devices are used. For example, a common setup of these devices is to rely upon a single active authentication scheme (such as a pin-lock or password) that is entered every time the device is activated for use. A 4-digit pin lock – while easier to enter quickly – offers little actual security value compared to most passwords (Chang et al., 2012), yet passwords – and particularly 'strong' passwords of sufficient length and complexity – are hamstrung by the difficulty of their swift and accurate entry on small 'virtual' keyboards (Angulo and Wästlund, 2012; Findlater et al., 2011).

The need for the development of effective user authentication mechanisms that offer actual security value while also addressing the needs of users and how these mobile devices are used is an issue of increasing significance, particularly given the value of personal data that is stored or accessible via these devices. However, and as a number of researchers have noted (e.g. Herley, 2014; Adams and Sasse, 1999) this effort must take a two-pronged but much more user-centric approach: users must be made aware of the importance of protecting their devices, but they must also be provided with the means of doing so that is appropriate for the ways in which these devices are used. By way of example, as these devices tend to be used frequently on the move and/or in short bursts, lengthy authentication procedures that require concentration or dexterity (e.g. one-handed virtual keyboard entry) are inappropriate. A consequence of authentication procedure design that fails to take into account the end user's needs is an entirely understandable but worrisome tendency for users to turn user authentication measures off (Clarke and Furnell, 2005).

Given the increased interactive affordances of touchscreens relative to physical keypads, many novel graphically based active authentication systems have been proposed (Sae-Bae et al., 2012; De Luca et al., 2012; Azenkot et al., 2012) as usable and secure alternatives to pin-locks and passwords. Oftentimes however, instead of reducing the potential for unauthorised access, many of these methods serve instead only to increase the range of attack vectors available to criminals. Notable recent examples include the 'smudge' attack (Aviv et al., 2010; Airowaily and Alrubaian, 2011) and the observation of key entry via 'shoulder surfing' (De Luca et al., 2012). Even the use of dedicated fingerprint scanners has been demonstrated as being easily defeated (e.g. Zhang et al., 2012, often by exploiting the same skin-oil deposits upon which the smudge attack relies.

An alternative solution is to include features of touch interaction dynamics as a *behavioural* biometric, for the principle reason that it is assumed that such behaviours would be more difficult for an attacker to consistently mimic. Some researchers, including De Luca et al. (2012), Angulo and Wästlund (2012) and Frank et al. (2013) have explored this in depth, reporting high levels of success using touch-behaviour based material to augment existing active authentication mechanisms. Others have presented entirely unique systems that are based on single or multi-touch gesture dynamic profiles (e.g. Sae-Bae et al., 2012; Feng et al., 2012) or through fusion with other sensory data such as accelerometers (e.g. Jain and Kanhangad, 2015) with similarly positive findings. Finally, researchers, including Shi et al. (2011), Bo et al. (2013), Damopoulos et al. (2013) and Li et al. (2013) have gone further still by developing touch-behavioural authentication systems that are entirely passive in nature, constantly monitoring touch interaction behaviour as a background process, invoking active authentication requests only when sufficient evidence has mounted that the active device user has changed.

Our work here however takes the use of touchscreen behavioural dynamics in a slightly different direction. While other work has considered the degree to which touchscreen gestural dynamics might offer value as a behavioural biometric for user authentication, relatively little attention has been given to what touchscreen gestures are able to reveal about the physical characteristics of their creator. Here then, instead of using touchscreen dynamics as a means of directly identifying an individual, we seek to establish whether links exist between these behavioural characteristics and other physical characteristics of the person behind the behaviours. Such a technique would be considered a 'soft' biometric in that we are seeking to identify a feature that is related to a group of individuals as opposed to a feature that is unique to an individual. While the potential for such techniques have been demonstrated using physical keystroke dynamics to predict a user's gender (e.g. Fairhurst and Da Costa-Abreu, 2011), to our knowledge, there currently exists no equivalent research on touchscreen gestural dynamics for this purpose.

1.4. Research questions

In this initial exploration, our overarching research question was to identify the degree to which a relationship exists between the length of a person's thumb and the resultant characteristics of touchscreen swipe gestures made with that thumb. To investigate this question, we first assumed that there would exist variance in swipe gesture characteristics. Further, we assumed that this variance would have two main sources: (1) the physical physiology of the user and (2) their individual level of touchscreen interaction skill/experience.

1.4.1. Physiology-based variance

The swipe gesture can be completed in one of four directions (left-right, right-left, down-up, up-down)[2]. For one-handed use, the performance of a swipe gesture requires various manoeuvres of the thumb, dependent upon the direction of the swipe and the hand in which the device is held. Specifically, two types of thumb movement are required for one-handed swipe gestures. These are flexion (bending)/extension (straightening) at the interphalangeal joint (the first joint from the thumb-tip), and palmar abduction (towards palm)/adduction (away from palm) at the carpometacarpal joint – the joint closest to the wrist. Again, assuming one-handed use, to swipe horizontally primarily demands palmar abduction/adduction, but will also involve some degree of supporting movement at the interphalangeal joint for precision i.e. to maintain a reasonably straight horizontal line. Conversely, vertical swiping demands more involvement of the interphalangeal joint. It is somewhat difficult (though not impossible) to perform vertical swipes using palmar abduction/adduction in isolation. We expected that these differences in manoeuvre would be detectable in the characteristics of swipe gestures on aggregate, hence:

Hypothesis 1: Different manoeuvres required for the thumb to swipe in different directions will result in differences in the characteristics of swipe gestures made in each direction.

Differences in the length of thumb also afford more or less ability to manoeuvre across the screen. Most obviously, a longer thumb can naturally and more easily reach further across the screen both horizontally and vertically. This we hypothesised would also be detectable, hence:

Hypothesis 2: People with longer thumbs will create swipes with different characteristics to people with shorter thumbs.

Supplementing hypothesis two, we also consider the fact that males have – on average – hands that are larger and thumbs that are longer than females. Given this known difference in thumb length across the biological genders, we hypothesised that males and females would generate swipes that are detectably different, hence:

Hypothesis 3: The characteristics of swipe gestures made by males will be different to those made by females.

Finally, and following our previous hypothesised differences in thumb manoeuvre, the hand in which the device is held is also potentially a factor in the eventual characteristics of a swipe gesture made in a given direction. Using the right hand, swipes in the D–U and R–L direction demand an initial flexion of the thumb at the interphalangeal joint prior to a 'pushing away' motion towards extension, whereas U–D and L–R swipes demand an initial extension of the thumb before 'pulling' the thumb across the screen. Using the left hand, these 'pushing' and 'pulling' manoeuvres for horizontal strokes will of course be reversed, hence:

Hypothesis 4: There will be differences in the characteristics of horizontal swipe gestures between left-handed device users and right-handed device users.

1.4.2. Previous experience with touchscreens

In the last ten years, touchscreen-based smartphones have rapidly become a ubiquitous feature of modern urban life. Interacting with a touchscreen efficiently is however a skill, and one that takes some time to develop fully. In light of this, and in combination with our main investigation into physiological differences of device users, we also considered the effect of user experience with current touchscreen technologies.

For finger-based operation of screens with ever increasing pixel densities, almost all smartphones now use capacitive touchscreen technology to provide a much higher sensitivity and accuracy than previous stylus-based resistive screen technologies. We expected that people with less experience with capacitive touchscreens (or indeed touchscreens in general) would exhibit a higher range of variance in their swipe patterns. Conversely, we expected experienced users to display a more habituated/stable gesturing pattern with smaller, more efficient movements and lighter pressures:

[2] Though technically feasible, triggering an onscreen action by diagonal swiping is very seldom used in mobile phone applications and as such is not considered in the present work.

Hypothesis 5: People with higher self-reported experience with touchscreens will produce more consistent swipe patterns, with lower levels of variance across their features on aggregate.

2. Method

A small software application was created to facilitate the systematic and controlled capture of swipe gesture samples in four directions. This application was deployed on a single reference touchscreen-based smartphone running the *Google Android* operating system.

2.1. Participants

178 participants ($m=87$, $f=91$) were recruited from the Universities of Bath and Southampton. The age range of our participant pool was between 18 and 59 years old, with 71% aged between 18 and 24 years old. At Bath ($n=61$), an opportunity-based sampling method was used and no reward was given for participation. At Southampton ($n=117$), participants volunteered their data as part of a larger data collection exercise for which they were paid. The collection methodology was identical in both cases. All participants were over 18 years of age, but no other participation eligibility criteria were applied. Of our participants, 161 used their right hand to complete the study and 17 used their left. Ethical approval for the study was sought and approved independently by the experimental ethics committees of the Universities of Bath and Southampton.

2.2. Apparatus and materials

All swipe gestures for this study were captured using a single reference smartphone device. The device used was a Samsung GT-I9100 'Galaxy S2' model smartphone, chosen for its high-resolution screen and high processor speed. The GT-I9100 has a 4.3″ capacitive touchscreen with a pixel density of 219 pixels-per-inch, providing an overall resolution of 480 × 800 px (W × H). All screen settings were set to the default values for the version of Android OS installed (2.3). No screen protectors were used.

2.2.1. The development of a touchscreen gesture recording tool

The requirements of our study demanded that we develop a systematic method for eliciting and capturing touchscreen swipe gestures made in four directions from a reference smartphone.

While it is possible to log all touch interaction events on an Android-based smartphone as a background process (i.e. regardless of the application currently in use), to do this requires maximum privilege, or 'root' level access to be made available on the device. As the process of obtaining root level access ('rooting') invalidates the device warranty, this method was not available to us. Without root level access, the recording of touchscreen interaction events is – for reasons of security – limited by the Android OS to a single application that must be custom built for this purpose.

For the purposes of our study, we required an application that would utilise multi-directional swiping as its primary interaction dynamic (so as to maximise our data yield). Common tasks, such as text messaging and internet browsing, do not utilise the swipe gesture to any great extent and were thus not considered appropriate options for further investigation. The potential of modifying an existing application such as the Android homescreen, photo browser or calendar systems was explored as they all use swiping for the purposes of navigation, but these options were later abandoned – primarily due to their very limited use of vertical swiping.

The final system that we developed for our data capture was a standalone Android application that used a tile sliding paradigm similar to that used to control the popular puzzle game 2048.[3]

Our chosen method presents a trade-off between ecological validity and experimental control that we recognise. However, we felt that this was the most appropriate method of collecting a controlled number of genuine swipe gestures from a large number of people without contaminating the data with other gestures (e.g. tap/double-tap), or by inadvertently directing participants to swipe from a particular point on the screen. Further, as all measures collected used standard methods of the Android SDK with no transformation or filtering applied (including details of the screen size, orientation and resolution of the reference device used), we are confident that the data collected here can be repeated, reproduced and built upon by other researchers who wish to use devices with more advanced screens than the Samsung i9100 used in this study.

To elicit swipe gestures in as unconstrained a manner as possible while still forcing the participant to swipe in several directions (specifically L–R, R–L, U–D, D–U), our gesture capture system was augmented with a simple reading task that was designed to produce a controlled number of swipe requests over all four directions. The task set to participants was to use the application to read a series of short jokes. Each joke (e.g. *what is the fastest thing in water?*) and its punch line (*a motor pike!*) were presented separately as simple slides. To progress through the slides, participants were required to perform a swipe gesture in the direction indicated on the screen. For the purposes of user feedback, upon completion of each slide the content of the slide would exit the screen in the direction that the swipe was made (Fig. 2).

2.2.2. Defining and capturing valid swipe gestures

For the operating system of our reference device (Google Android), a swipe gesture interaction is triggered (and subsequently recorded by our application) upon satisfaction of two parameters that must be specified at the application level. These are (1) a minimum value for length (measured in pixels) and (2) a minimum value for velocity (measured in milliseconds). As screen sizes and pixel density vary widely across smartphones, there currently exists no standard value for these parameters. For the purposes of the study, the minimum length was set at 120 pixels and the minimum velocity was set at 200 ms. These values were suggested by the Android software development community as being commonly used values, and are based upon those used on the default Android OS home-screen. A series of pilot studies of gesture captures conducted with six users indicated that, in practice, the distance travelled during a typical swipe gesture is typically several times this minimum figure, and had no identifiable impact on the way that participants completed their gestures.

Upon capture of each gesture sample, all raw data that could be captured about it was recorded and sent immediately to a central database via Wi-Fi. All measure were captured using the standard touchEvent methods provided by the Android software development toolkit. Custom built web-based software automatically analysed the incoming gesture data, producing a set of calculated metrics along with the ability to immediately reconstruct each gesture to scale as a vector graphic (Fig. 3). The ability to immediately and visually inspect each swipe gesture proved to be extremely useful in accurately identifying software recording errors and other potential data contaminants.

2.2.3. Swipe gesture feature extractions

Each swipe gesture generates a series of time-stamped points that together trace the path of the gesture as it travels across the screen.

[3] The mobile version of 2048 (http://2048game.com/) uses multi-directional swiping to replicate the arrow-key controls used in the desktop computer based version.

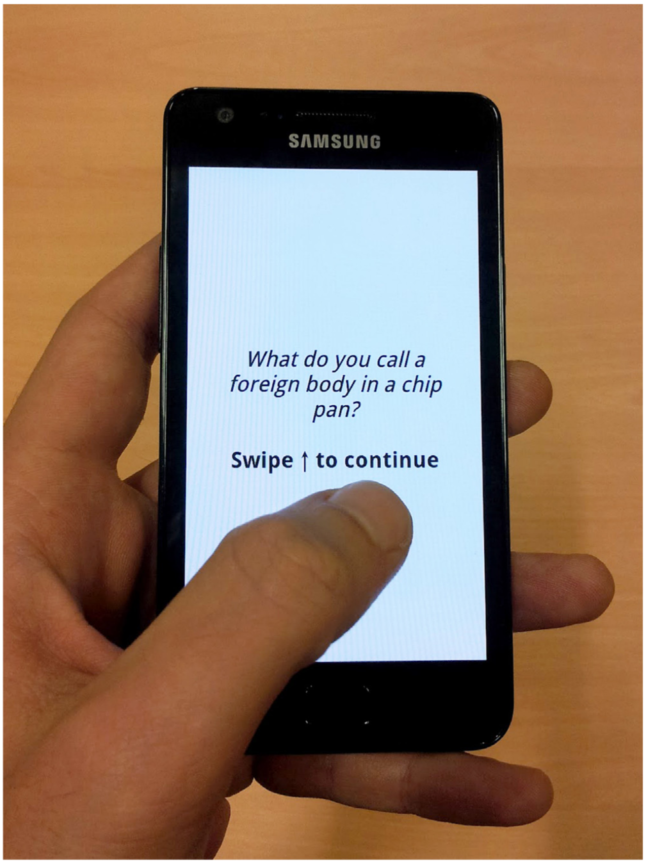

Fig. 2. Swipe gesture capture application. Participant is instructed to swipe in the direction indicated.

From each recorded gesture, six features were extracted and/or calculated. These feature were felt to adequately cover the main dimensional features of the swipe gesture and are described thus:

1. *Gesture length (pixels):* calculated by summing the Euclidean distances between each of the internal path-points.
2. *Gesture completion time (ms):* i.e. from initial screen contact to finger release.
3. *Avg. gesture thickness (px): thickness* here refers to the approximated amount of skin surface area that was detected as being in contact with the screen as the swipe gesture path was created. A final value was obtained for each gesture by obtaining the averaged thickness value across the gesture path as a whole.
4. *Avg. applied touch pressure*: the Android SDK reports a normalised value between 0 and 1 for pressure applied to the screen at each path point. As with gesture thickness, we took the averaged value for the entire gesture path for this measure.
5. *Max. speed achieved (cm/sec):* a simple conversion from pixels to cm was obtained via measures of the screen dimensions and known dots-per-inch.
6. *Max. acceleration achieved (cm/sec2):* calculated as final velocity initial velocity/time.

For the purposes of reproducibility, all data relating to touch interaction events, including timing information, were collected via methods supplied by the Android OS *motionEvent* class.[4] *X* and *Y* co-ordinates were collected using the *getRawX* and *getRawY* methods respectively. During data collection, all user controllable applications on the device were shut down prior to launching our custom gesture recording application.

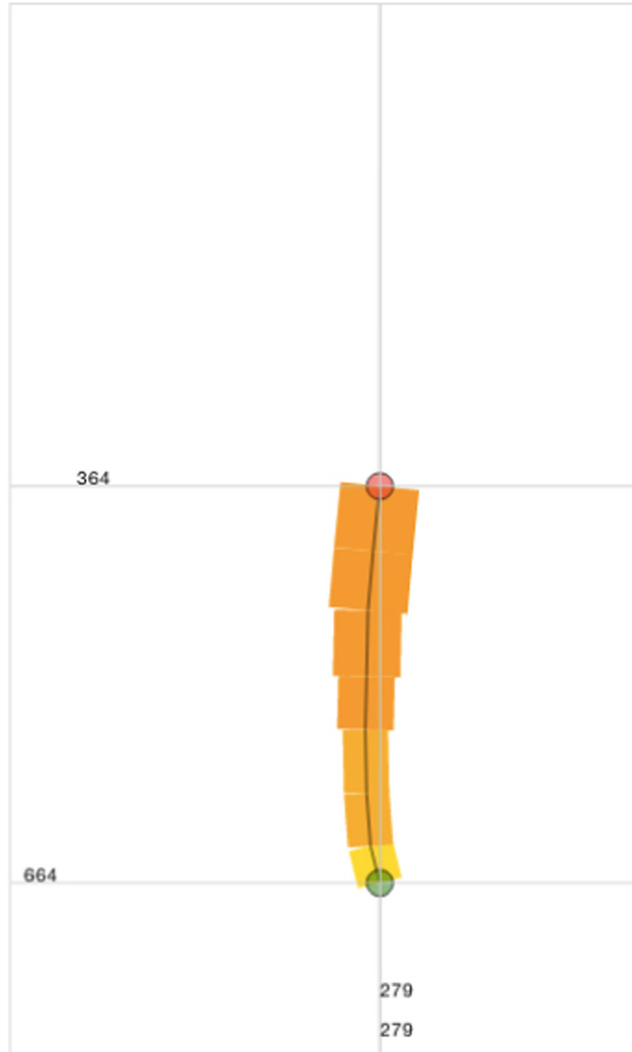

Fig. 3. A complete D–U swipe represented as a scaleable vector graphic (SVG). Touch pressure is represented by colour: yellow (low) through red (high). (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this paper.)

2.3. Procedure

Each participant was first provided with written instructions detailing the requirements of the study, after which their signed consent was obtained. Participants were then asked to provide details of their biological gender, phone handedness[5] and the length of their thumb (mm). The length of the thumb was measured from the carpometacarpal joint (closest the wrist) to the thumb tip, with the thumb at full extension. Finally, we asked all participants to self-report their prior experience with touchscreen-based smartphones, using a 6 point Likert scale (1: no prior experience to 6: highly experienced).

The participant was then presented with the instrumented smartphone and the researcher demonstrated the swipe gesture. In order to maximise consistency in our sample set and to provide

[4] Details of the Android SDK motionEvent class and its methods are available at http://developer.android.com/reference/android/view/MotionEvent.html

[5] *Phone handedness* here specifically referred to the hand that the participant used to complete the study. However, we also recorded their true dominant handedness if different.

the best possible conditions for linking our known physical measurement of thumb length to subsequent touch screen interactions, for this study the orientation of the screen was fixed to portrait mode and interactions with the screen were restricted to single-handed use only (participant's preference), using only the thumb of that hand to interact with the screen. Future work will seek to establish the degree to which two handed operation impacts on our findings here.

Prior to completing the study, each participant was allowed a few moments to familiarise themselves with the device and the generation of swipe gestures by navigating menus on the home-screen and browsing the Internet. These applications were then shut down, and the participant was then instructed to launch the gesture recording application, following the instructions provided on the screen. Participants were instructed to complete the task using only the thumb of one hand (their choice) to generate each swipe gesture.

The order of slide presentation (and by extension the direction of swipe required to progress through the slides) was randomised for each participant. In total, each participant submitted 120 swipe gestures (30 samples in each direction). The total duration of the study was between 10 and 15 min, after which all participants were fully debriefed.

3. Results

A total of 21,360 individual swipe gestures were collected from 178 participants, with each participant providing 30 swipe gestures for each of four directions (U–D, D–U, L–R and R–L). Prior to analysis, 2207 samples were identified as containing extreme outliers on at least one measure and were removed, leaving a final dataset of 19,153 samples.

Exploration of the data revealed a non-normal distribution for all six of our feature extractions. Normalisation of the data for each feature was attempted using logarithmic and square transforms to reduce skew where appropriate. However, subsequent examination of the Kolmogorov–Smirnov and Shapiro–Wilk tests of normality indicated that both remained highly significant, and Levene's test for homogeneity of variance also failed for all features, regardless of transform. Consequently we chose to employ non-parametric data supportive statistical tests in all subsequent analyses of swipe gesture characteristics.

3.1. *Previous experience with smartphones and the relationship between experience and intra-participant gesture feature consistency*

On a scale of 1 (no experience) to 6 (highly experienced), 72% of our participants self-rated their level of experience with touchscreen-based smartphones at 5 or above, while only 2.8% reported as having no prior experience with this technology. A statistically significant difference was observed in self-reports of touch screen experience for males and females, with males (M=5.02, SD=1.2) rating themselves slightly higher on average than females (M=4.51, SD=1.42), one-way ANOVA: $F(1{,}176)=6.88$, $p<0.01$. A question arises as the whether this difference in self-rated scores has a direct impact on actual performance at completing swipe gestures. From observations of our participants as they completed the study, we found no evidence of difficulty interacting with the screen. We instead suspect that the more conservative scores reported by our female participants is related to a perceived technical ‘confidence gap’ across the genders that is unfounded. In summary, and particularly given that both male and female scores for experience were very high, we consider the impact of this gender difference upon our broader research questions as minimal.

Spearman rank order correlation revealed no significant relationship between participant age and touch screen experience ($r_s(178)=-0.06$, $p=0.40$ n.s.), though this result needs to be considered with caution given that the majority of our participants were less than 25 years of age.

To examine the relationship between self-reported touchscreen technology experience and swipe gesture consistency, we first calculated the total variance for each of the six features across all of the gesture samples provided by each participant. These values were then examined against their self-reported levels of touchscreen-based smartphone experience using the Spearman RHO correlation coefficient procedure.

Our *Hypothesis* 5, *people with higher self-reported experience with touchscreens will produce more consistent swipe patterns*, was partially supported. Spearman RHO revealed weak but statistically significant relationships between self-reported levels of touchscreen-based smartphone experience and the variance of three of our six features, providing some evidence that swipe gestures do become more internally consistent as experience with touchscreen operation increases. Intra-participant variance in gesture length ($r_s(178)=-0.163$, $p=0.03$) and completion time ($r_s(178)=-0.189$, $p=0.01$) were observed to reduce as self-reported experience increased, while max. accelerations achieved were observed to increase with experience ($r_s(178)=-0.208$, $p<0.01$). No significant relationship was observed between self-reported levels of touchscreen-based smartphone experience and intra-participant variances in max. speed, gesture thickness or applied touch pressure.

3.2. *The effect of direction upon swipe gesture characteristics*

A Kruskal–Wallis test was conducted to determine if there were significant differences in our six measures across the four directions of swipe captured. Post hoc pairwise comparisons were performed using Dunn's procedure, with a Bonferroni correction for multiple comparisons applied.

Our *Hypothesis* 1, *different manoeuvres required for the thumb to swipe in different directions will result in differences in the characteristics of swipe gestures made in each direction*, was partially supported. The Kruskall–Wallis test revealed a significant omnibus effect of direction on all six of our gesture feature extractions. Post hoc analysis further revealed statistically significant differences at the 0.05 level for all features between almost all direction pairs. These differences suggest that the direction in which a swipe is drawn is an important factor in its resultant characteristics, and that any further analysis of swipe gestures should take these directional differences into account. However, there were instances where particular characteristics did not differ across specific direction pairs that are important to note: gesture lengths for swipes drawn in the vertical directions (U–D and D–U) were not significantly different from one another, and completion times for swipes drawn in the horizontal directions (R–L and L–R) were also statistically indistinguishable from one another in our sample.

3.3. *Differences in horizontal swipe gesture characteristics between left and right handed device users*

Median values for all six measures were compared between participants who held the device in their left hand and participants who used their right hand using the Mann–Whitney *U* Test procedure. All pairwise comparisons were again performed using Dunn's procedure with a Bonferroni correction for multiple comparisons applied. Our *Hypothesis* 4, there will be differences in the characteristics of horizontal swipe gestures between left-handed device users and right-handed device users was supported. Mann–Whitney revealed that swipes created by left-handed device users exhibited lower completion times and higher speeds than right-handed device users for swipes made in the R–L direction (where completing the gesture demanded that the thumb be extended first before being pulled across the screen), whereas right-handed

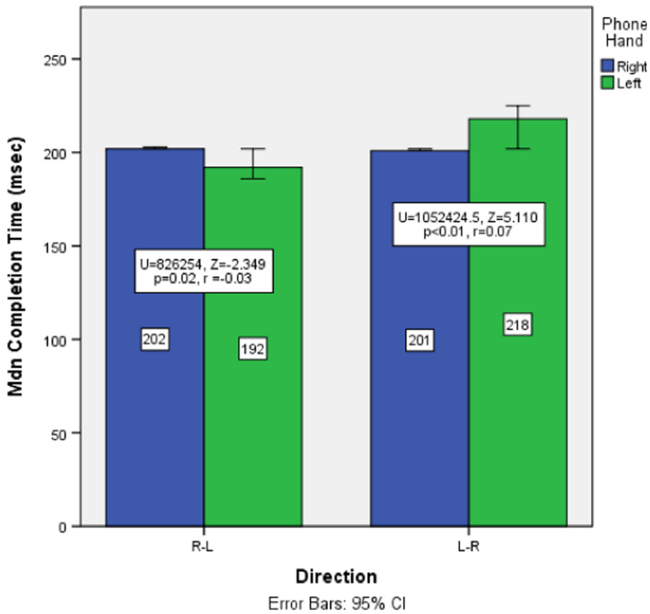

Fig. 4. Median completion times for horizontal swipes that were created using the left and right hand.

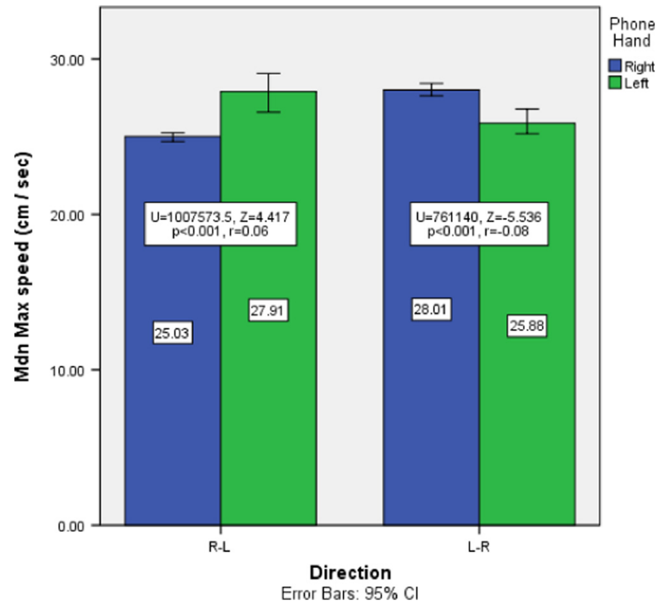

Fig. 5. Median maximum speeds achieved for horizontal swipes that were created using the left and right hand.

device users outperformed left-handers on the same measures with swipes made in the opposite L–R direction. These differences were observed as being statistically significant at the 0.05 level. Median completion times and maximum speeds for left and right handers across the two directions of horizontal swipe are presented in Figs. 4 and 5 respectively.

Post hoc analysis also revealed several other statistically significant differences in gesture characteristics that were related to handedness but limited to specific directions of swipe. Right handers were observed to create longer L–R 'pulling' swipes than left-handed device users (Mdn[left]=250.00, Mdn[right]=252.00, U=860823.5, $Z=-2.095$ p=0.04), and right handers created thicker R–L 'pushing' swipes than did left handers (Mdn[left]=43.4, Mdn[right]=44.4, U=819043, $Z=-2.823$, p=0.005). Conversely, left handers applied more pressure on L–R 'pushing' swipes (Mdn [left]=0.225, Mdn[right]=0.214, U=999993.5, Z=2.960, p=0.003). No differences were observed for maximum accelerations achieved.

3.4. The relationship between thumb length and resultant swipe characteristics

3.4.1. Linking thumb length and swipe characteristics

A revised and more accurate method for collecting thumb lengths was used in the second data collection at Southampton (n=116). Our revised thumb measurement protocol was developed in collaboration with forensic anthropologist Prof. Sue Black (University of Dundee, U.K.). Under her advisement, in the second (Southampton) data collection, our measurement of thumb length was taken from the carpometacarpal joint (closest the wrist) to the joint tip. For each participant in the Southampton data collection, high resolution scaled photographs of both hands were collected under controlled conditions for reference, and all measurements were completed by the same person. In the first collection (Bath) we took only a manual measurement from the adjacent metacarpophalangeal thumb joint to the tip, without collecting a photographic reference. This change in procedure rendered the two measurement sets incompatible with one another. As result of this, thumb length measures from the Bath dataset (n=61) have been excluded from this analysis.

Participant thumb lengths (n=116) ranged from 9.8 cm to 14.1 cm (M=11.8 cm). Following population trends, male thumbs (M=12.4 cm, SD=0.62) were on average longer than females (M=11.2 cm, SD=0.53) in our sample. This difference was found to be statistically significant at the 0.05 level (one way ANOVA: F (1,114)=39.75, $p<0.001$).

To examine the relationship between thumb length and swipe gesture characteristics, we compared each of our six features with thumb length using the Spearman RHO correlation coefficient procedure.

Our *Hypothesis* 2, *people with longer thumbs will create swipes with different characteristics to people with shorter thumbs*, was supported by three of our measures. Spearman's RHO revealed a statistically significant relationship between thumb length and the following features of swipe gesture:

Completion times were observed as being related to thumb length ($r_s(115)=-0.305$, $p<0.001$ two-tailed), showing that as thumb lengths increased, the completion time for swipe gestures decreased (Fig. 6).

Maximum speeds were observed as being related to thumb length ($r_s(115)=0.268$, $p<0.01$ two-tailed), showing that as thumb lengths increased, the maximum speed achieved increased (Fig. 7).

Finally, maximum accelerations were observed as being related to thumb length ($r_s(115)=0.265$, $p<0.01$ two-tailed), showing that as thumb lengths increased, maximum acceleration increased (Fig. 8).

No significant relationship was observed between thumb length and gesture thickness, avg. pressure or gesture length.

3.4.2. Linking swipe characteristics to gender

A comparison of the median values for our six measures between our male and female participants was performed using the Mann–Whitney U Test. Pairwise comparisons were again performed using Dunn's procedure with a Bonferroni correction for multiple comparisons applied.

Our *Hypothesis* 3, *the characteristics of swipe gestures made by males will be different to those made by females*, was partially supported. Building upon the correlations that we observed for thumb lengths, the Males in our sample completed swipe gestures faster than the females in all directions, and this was again observed in terms of shorter completion times (Fig. 9), higher speeds (Fig. 10) and higher accelerations (Fig. 11). An additional difference between the genders was also observed in that males

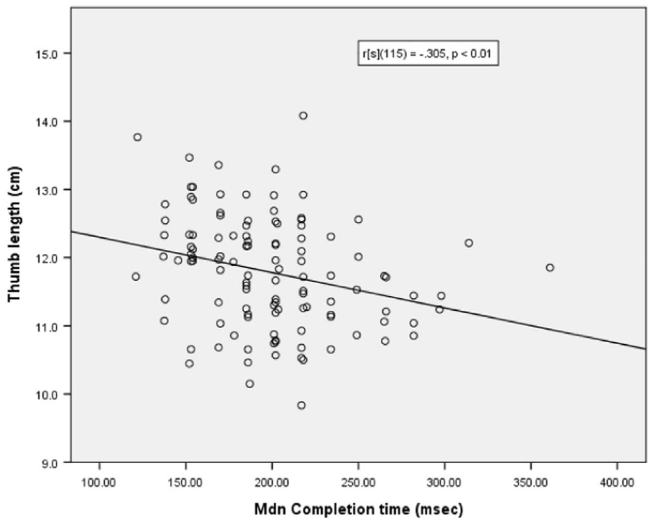

Fig. 6. Scatterplot of thumb length and median gesture completion time.

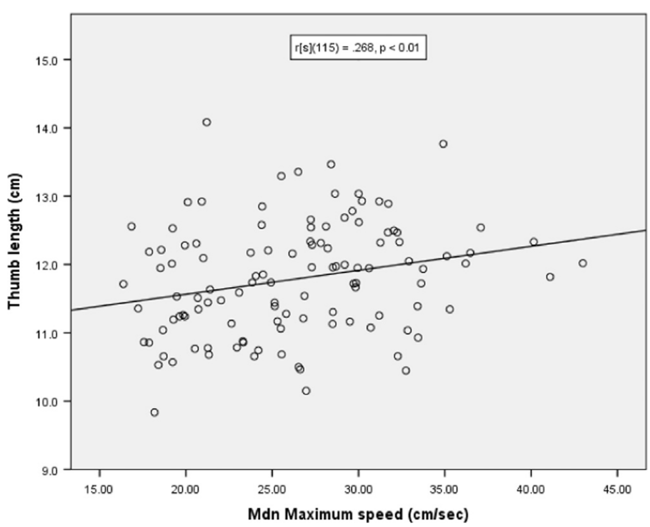

Fig. 7. Scatterplot of thumb lengths and median maximum speed.

were found to apply more pressure to the screen than did females, across all directions of swipe (Fig. 12).

No statistically significant differences were observed for gesture lengths or gesture thicknesses between males and females in any direction of gesture.

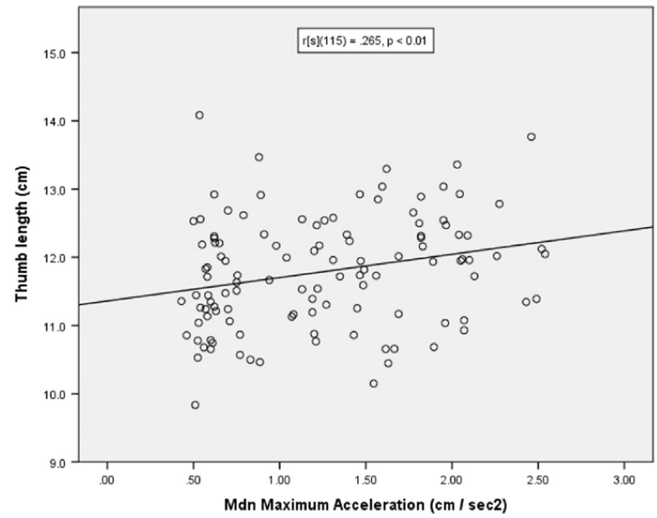

Fig. 8. Scatterplot of thumb lengths and median maximum acceleration.

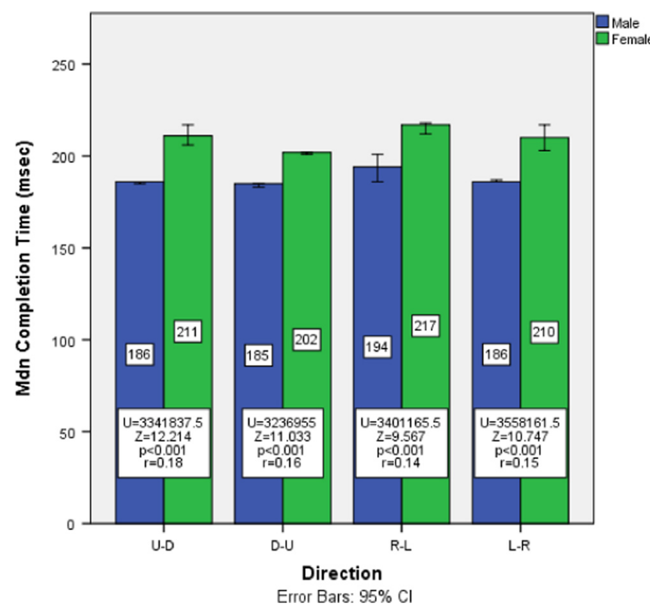

Fig. 9. Completion time by gender.

4. Discussion

In this paper, we present an initial investigation of the relationship between six touchscreen swipe gesture characteristics and a specific physical characteristic of their creator: the length of their thumb. Should such a relationship exist, we suggest that this could – via following the known proportional relationships between human segment lengths – offer a route to inferring other measures of a given user's physical characteristics, such as their standing height or foot size. This work was inspired by a known problem in contemporary criminal investigations: how to identify criminals who conduct their activities using temporary ‘burner’ mobile phones that are unregistered to them by name. Within this scenario, we suggest that the ability to link physical characteristics to behavioural metrics captured from the way in which a person interacts with a touchscreen device could prove useful to law enforcement analysts as they begin eliminating groups of potential suspects towards the identification of a specific individual.

From an analysis of approximately 19,000 swipe gestures supplied by 178 participants, we show that there is a relationship between thumb length and three features of swipe gestures. Our analysis thus far has shown that users with longer thumbs complete swipe gestures with shorter completion times, higher speeds and higher accelerations than users with shorter thumbs. Further supporting these findings, these differences in swipe composition were also observed to exist between our male and female participants, where there is a known difference in thumb length within the general population (males on average having longer thumbs than females). Finally, while no relationship was found between thumb length and touch pressures applied during swipe gesture composition, we did observe a statistically significant difference between males and females (males apply more touch pressure than females, regardless of swiping direction), suggesting that other physiological factors relating to larger hands – such as variance in grip strength – might also be detectable.

That our two remaining features (swipe gesture length and thickness) were not found to be useful indicators of the physiological characteristics of their creator's thumb was unexpected. Gesture length

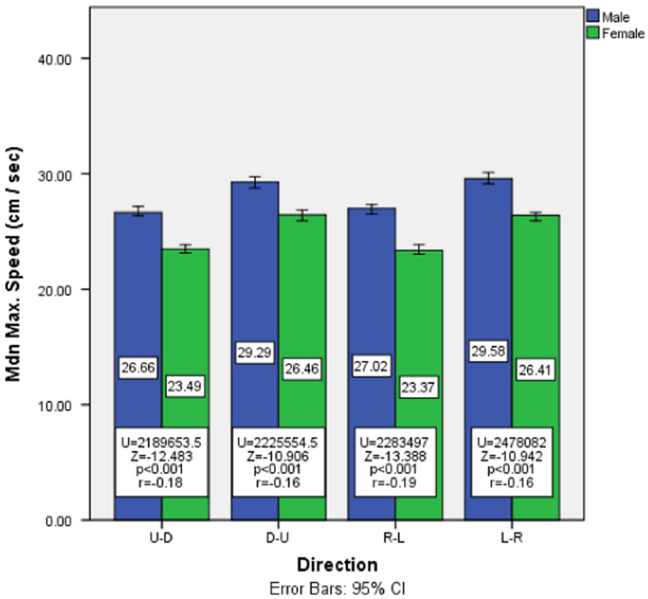

Fig. 10. Maximum speed achieved by gender.

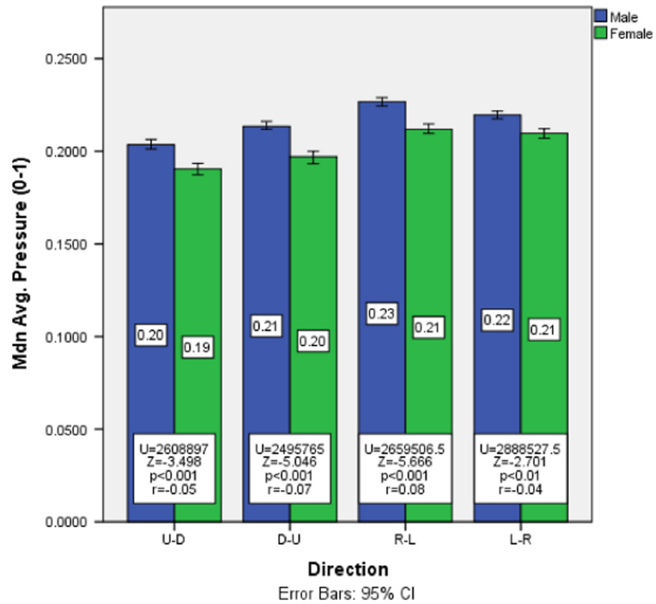

Fig. 12. Average touch pressures applied by gender.

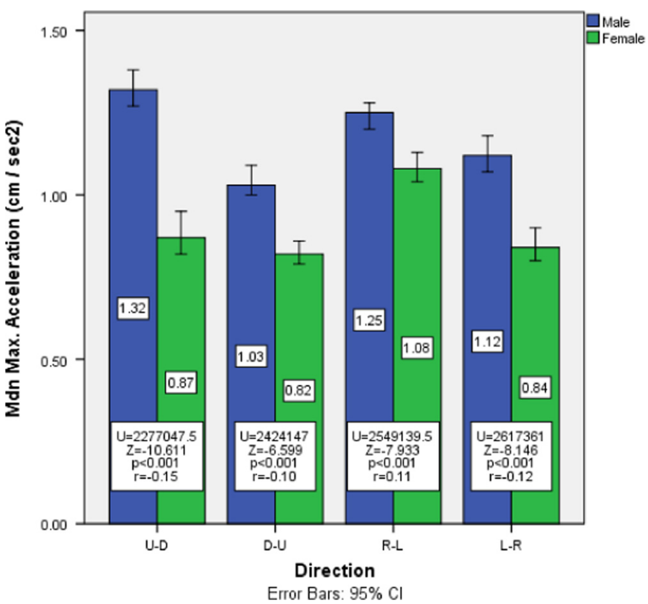

Fig. 11. Maximum acceleration achieved by gender.

in particular was surprisingly unfruitful given the reasonable assumption that a longer thumb affords an increased range of motion that we expected would result in longer swipes. However, from what we have seen of the swipe gesture in practice, the length of a swipe gesture is actually too short for longer thumbs to be of any detectable benefit.

Also contrary to our initial expectations, participants in our sample did not create swipe gestures as efficiently or as consistently as we assumed they would. However, we did find some evidence to suggest that increased experience with touchscreens reduced intra-participant variance in some the features we examined, namely that higher self-reported experience was weakly correlated with swipe gestures of a higher efficiency (shorter lengths, faster completion times and higher accelerations). However, we must currently treat this finding with some caution given that our participant pool was heavily skewed toward younger smartphone users.

4.1. Lessons learned

Through the course of the collection and analysis of the large dataset collected during the study, there were a number of lessons learned from our experience that will inform our future work and would be of benefit to other researchers and practitioners working in this area.

Firstly, both intra- and inter-participant swipe gesture data is somewhat noisy, with all of our measures following a non-normal distribution. The non-normal nature of the data placed limitations upon the statistical tools that could be appropriately used to perform our analysis, particularly with regard to predictive modelling techniques such as regression. While machine learning algorithms potentially offer an alternative predictive route (and one we are actively investigating), there exists significant risk of both type I and II error in datasets of this type if inappropriate statistical tools are applied. Researchers are encouraged to be mindful of this.

Further, researchers are encouraged to be mindful to pay particularly close attention to the impact of extreme outliers in touchscreen interaction data at the level of gesture capture. Though rank-order based statistical analysis that focus upon median values rather than means are better suited to mitigating the effect of outliers, examination of our data prior to analysis indicated that we needed to discard some 10% of our results due to the presence of extreme outliers on at least one of our measures. Identifying reasons and developing countermeasures for these extreme values to maximise data yields is the focus of continuing investigation. Some are certainly due to the intermittent software level recording error that we mentioned in our results. These are relatively easy to identify and discard as they occur as they all have clearly identifiable breaks in their internal path sequence identifiers. However, others appear to be valid swipes in all respects other than that they have characteristics that fall far outside the 'normal' range of their creator. A full appreciation of the reasoning behind these intermittent 'extreme' swipe patterns is far from complete, but we suspect that at least some are the result of an over-compensation immediately after a recording error (i.e. as the participant received no feedback that the swipe gesture was recognised, they immediately re-doubled their efforts in the next swipe attempt leading to a far longer/higher pressure swipe gesture). More work is required both to finesse the gesture collection technique we have developed and to evaluate the impact that these errors have.

Secondly, our analysis thus far indicates clearly that the direction in which the swipe is drawn does affect its characteristics, thus swipe gesture patterns should be analysed separately on a per-direction basis. Similarly, left and right handed device users exhibit differences in swipes made horizontally. Both of these factors should be controlled for when analysing swipe data characteristics at the aggregate level.

Thirdly, and though care was taken to clean the screen of our reference device regularly between collection sessions, a rapid build up of skin oils on the screen was still observed. Indeed, we suspect that a source of some of the noise encountered in our data was due to variances in skin/screen friction as a result of the build up of skin oils. Further, and though we ourselves did not use any aftermarket screen protectors, we recognise that many device users do fit such devices. Further investigation is required to understand the degree to which these factors affect the characteristics of swipe gesture composition and – if necessary – how these effects be detected and controlled for.

Finally, we must accept that our initial methodology for collecting measurements of thumb length lacked sufficient rigour, resulting in the loss of a significant amount of data. It is apparent that techniques for collecting anthropometric data vary widely, and a discussion of the relative accuracy of various techniques (e.g. manual calliper vs. imaging, the identification/selection of external joint/skinfold landmarks) is ongoing. Researchers are strongly encouraged to seek advice from the medical and forensic research communities before gathering data of this type.

4.2. Limitations of the research

In discussing the conclusions of our research thus far, we must of course be mindful of the potential future applications of any system that relies upon indirect measures in order to draw inferential conclusions about people. This is of particular importance here given that there is obvious potential for gesture data collection to be conducted covertly without knowledge or consent. While a full discussion of the privacy implications involved in developing such techniques is outside the scope of this paper, it is important to be very clear that this work – currently in its infancy – has significant privacy issues attached to it and is some considerable distance from deployment in a real-world scenario.

Therefore, while we feel that our results presented here offer an encouraging first step towards our ultimate goal, we stress the limits of our findings thus far, particularly given the limited choice of hardware examined and the restricted interaction mode imposed upon our participants. To restate our main objective, the aim of the present work was to explore whether it is feasible to link touchscreen gesture characteristics to the thumb length of their creator, as a precursor to the detailed and significant amount of further work that would be required to operationalise such links for use in a forensic context. So far, we have found evidence to support the presence of relationship between several features of the swipe gesture and thumb length, but note that this relationship is currently only useful as an indicator when considered relative to population averages (as opposed to revealing the actual length of a particular user's thumb). Further, the data collection method was conducted under controlled laboratory conditions. Much more research is required to establish a means of inferring actual thumb length to any degree of accuracy, particularly when taking into account the myriad devices available and the many ways in which people choose to interact with these devices. To this end, we highlight below several limitations of our research that will be the focus of attention in our future work.

Firstly, we accept that our findings are currently limited to one specific mobile device that was held and operated in a very specific way (our participants were forced to hold our instrumented smartphone in one hand, using only their thumb to interact with the device). This we argue was necessary at this early stage to maximise any potential correspondence between thumb length and touch gesture characteristics. However, we do of course recognise that these devices can and often are operated with both hands and with other digits than the thumb. Further work will seek to address this by allowing participants to choose the way in which they hold the device and the digit that they use to interact with the screen.

Secondly, there are limitations to our sampling method. While the effect of both physiological differences and performance factors related to past experience with touchscreens was considered in our analysis, as a result of using an opportunity-based sampling method, the majority of our participants were young adults. Most of our participants were highly experienced touchscreen operators. Despite this however, we did still observe a weak but statistically significant signal in our less confident participants, indicating that lower touchscreen technology experience may well effect the stability and consistency of swipe gestures over time – particularly as novices become more adept at using the technology. The development of our future recruitment strategy will address this issue by substantially increasing the range of age and experience in our population sampling method.

Finally, in this study we collected only 120 gesture samples from each participant within a single session. Given that we now know that direction is important, future work would certainly seek to increase the number of samples that we collect in each direction, perhaps by instrumenting a game (such as the previous puzzle game 2048 mentioned previously) that uses multi-directional swipe as its main control. Future work will seek to capture multiple gesture samples over a number of sessions in order to develop a better understanding of individual gesture consistency over time.

5. Conclusions and future work

Our results thus far offer positive signals that a route between a behavioural biometric and a physical biometric is potentially available via features of a common touchscreen interactional gesture. Our work so far has uncovered some evidence to support the notion that a physical characteristic of a person – namely their thumb length relative to population trends – could be detectable from characteristics of their behavioural touchscreen interactions.

Future work will build upon the relationships we have observed here, and will seek to examine other feature extractions along with assessing the predictive capability of the features we have examined thus far. Future studies will also seek to increase our population sample and to examine free input (using finger instead of thumbs) along with devices of different form factors.

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